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DE-NOISING PADDY SEED IMAGES BY NOISENIXIE REJUVENATION FILTER: A NOVEL PREPROCESSING ALGORITHM FOR ENHANCED IMAGE QUALITY

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Abstract

The digital age thrives on image processing, a technology critical for healthcare and security. This paper proposes a robust approach to improve image quality and empower further analysis through innovative preprocessing techniques. Our approach attempts to implement image data systematically, ensuring it's ready for advanced processing. Standardization with Bicubic Interpolation: Input images are resized to a uniform dimension using Bicubic Interpolation. This ensures compatibility within datasets, regardless of their original sizes, while preserving the image's proportions. Separating Brightness for Sharper Analysis: Images are converted from RGB to YCbCr color space. This separates the image data into brightness (luma) and color (chrominance) components. Focusing on the bright information is crucial for noise reduction and edge detection. Enhanced Clarity with NoiseNixie Rejuvenation Filter: Our novel NoiseNixie Rejuvenation Filter (NNRF) tackles noise, a standard image quality hurdle. This filter incorporates noise variation and light correction adjustments, resulting in sharper and clearer images. Fast Fourier Transform for Refined Processing: The Fast Fourier Transform (FFT) converts image data into the frequency domain. This transformation unveils hidden patterns within the image and allows for precise adjustments. The data is then converted back using the Inverse FFT, preparing the image for in-depth analysis. By implementing these techniques, our preprocessing pipeline empowers researchers and practitioners to unlock valuable insights from image data. This comprehensive approach paves the way for advancements in image processing across various applications. From medical imaging to autonomous vehicles, high-quality image analysis is essential, and this method provides a robust foundation for achieving that goal.

Keywords:

Paddy Seed, Imaging, NoiseNixie, Rejuvenation Filter

1. INTRODUCTION

The assessment of the world’s most crucial staple food crop’s quality relies on the characteristics of its grain, including shape, size, and texture. In India, where the population is continually growing, losses in handling and processing, coupled with heightened expectations for high-quality and safe food products, underscore the necessity for accurate, rapid, and objective quality determination of food grains. Currently, chemical methods are employed to identify rice grain seed varieties and assess quality [1]. However, these methods have drawbacks, as they destroy the sample and consume a considerable amount of time. Conversely, machine vision or digital image processing emerges as a non-destructive, swift, cost-effective chemical method alternative. In the initial stages of applying machine vision to evaluate grain quality, Lai et al. [2] proposed various pattern recognition techniques for identifying and classifying cereal grains. This technology offers a more efficient and practical approach to assessing the quality of food grains compared to traditional chemical methods.

Rice holds paramount importance for people worldwide. Efficient classification of rice seed varieties is critical to ensuring quality inspection [3]. Technicians rely on experience to assess color, shape, and texture similarities to perform this task manually. Consequently, we advocate exploring a systematic approach to automate the rice recognition process. Enhancing productivity in agricultural production necessitates a focus on speed and accuracy for sustained economic growth, competitiveness, and sustainability over the long term [4]. Conventional manual operations for classifying paddy rice seeds prove costly and unreliable. This unreliability stems from the inconsistency, subjectivity, and slowness inherent in human decisions when identifying objects and issues [5].

In the era of digital transformation, image processing has become a cornerstone for applications in healthcare, agriculture, and security. The assessment of agricultural products like rice, a staple food for billions globally, relies heavily on analyzing grain characteristics such as shape, size, and texture. In India, where food demand continually rises, efficient grain quality assessment is paramount for ensuring food security and sustainability. Traditional chemical methods, although reliable, are destructive, time-consuming, and resource-intensive. This necessitates the adoption of advanced, non-destructive techniques like digital image processing to enhance efficiency, accuracy, and cost-effectiveness in grain quality inspection. Automated systems leveraging machine vision offer an innovative approach to address these challenges by delivering rapid, objective, and consistent results. In response to this challenge, machine vision technology emerges as a viable alternative, offering automated processes that are non-destructive, cost-effective, and capable of delivering rapid and accurate results [10].

2. EXISTING WORK

Rice, a staple food for billions, demands efficient quality evaluation methods. Traditional manual inspection is time-consuming and subjective. Machine vision offers a powerful alternative, transforming rice quality assessment.

Researchers like Sindhu et al. [6] explored image-processing techniques to classify rice varieties and assess purity. Their work highlights the potential of analyzing features like grain shape and color for automated quality control.

Hoang et al. [7] pushed the boundaries further. They compared various methods for rice seed classification using the VNRICE dataset. Their findings demonstrate the remarkable accuracy (99.04%) achieved with DenNet21, a deep-learning architecture. This signifies a significant leap towards fully automated rice seed variety identification.

Another study by Kiratiratanapruk et al. [8] delved into classifying 14 Oryza sativa rice varieties using machine vision. Their work encompassed three key stages: Preprocessing:

Ensuring consistent seed orientation for accurate analysis. Quality Screening: Identifying and removing abnormal seed samples. Feature Extraction and Classification: Data on shape, color, and texture were extracted to represent each seed. This data was then classified using various machine learning and deep learning techniques.

The study compared the performance of four statistical machine learning methods (Logistic Regression, linear discriminant analysis, k-nearest Neighbors, and Support Vector Machines) with five pre-trained deep learning models (VGG16, VGG19, Xception, InceptionV3, and InceptionResNetV2). Interestingly, the Support Vector Machine achieved high accuracy (up to 90.61%) for subgroup classification, while deep learning models, particularly InceptionResNetV2, excelled at collective group classification (reaching 95.15% accuracy) [11]-[20].

Despite their utility, traditional chemical methods for grain quality analysis face several drawbacks. These methods not only destroy the sample but also demand substantial time and resources, limiting their scalability. Manual inspection, while non-destructive, suffers from inconsistency due to subjectivity, human error, and fatigue, making it unsuitable for large-scale operations [21]. Existing machine vision approaches, though promising, often encounter limitations in preprocessing and noise reduction, leading to compromised image clarity and accuracy. Furthermore, the lack of robust and efficient algorithms for feature extraction and classification hinders their widespread adoption in real-world agricultural settings. Overcoming these limitations necessitates the development of advanced preprocessing techniques and automated systems to ensure high-quality and reliable outcomes [22]-[24].

These studies showcase the immense potential of machine vision in rice quality assessment. By automating classification and purity analysis, machine vision promises to enhance the rice industry’s efficiency, precision, and consistency.

3. DEEP LEARNING ENHANCES RICE QUALITY ASSESSMENT IN TAMIL NADU

Rice, a staple food for billions, is particularly crucial in Tamil Nadu, a leading rice producer in India. Often called the “Rice Granary of South India,” Tamil Nadu cultivates 400 rice varieties [3]. These include traditional landraces like Seeraga samba, Madumuzhungi, Kuzhiyadichan, and Poongar, which hold immense value for preserving genetic diversity and unique traits.

However, rising concerns about soil erosion and the shift towards high-yielding varieties necessitate the urgent collection and conservation of these indigenous rice varieties. This effort is vital to maintaining these traditional landraces’ genetic richness and unique characteristics, ensuring the long-term sustainability of rice cultivation in Tamil Nadu.

Machine vision, specifically deep learning techniques, offers a powerful tool to achieve this goal. Research by Patel et al. [9] proposed a deep learning-based method for classifying rice types. Their approach utilizes two methods:

- **Deep Convolutional Neural Network (CNN)**: This method trains a CNN using segmented rice grain images for classification.
- **Hybrid Model with Transfer Learning**: This method leverages a pre-trained VGG16 network combined with a new approach for classification. Transfer learning allows the model to benefit from the knowledge gained by the pre-trained network, ultimately improving accuracy.

This research goes beyond rice type classification and addresses the classification of broken or whole grains. Their 5-class model, trained on 4000 images, demonstrates the potential of deep learning for comprehensive rice quality assessment. Before classification, paddy seeds require pre-processing to remove noise and enhance image quality. This pre-processing step ensures accurate analysis using the deep learning model. By implementing deep learning-based rice quality assessment, Tamil Nadu can significantly improve the conservation efforts for its traditional rice landraces. This technology facilitates the efficient classification of rice varieties and broken grains, enabling the collection and preservation of valuable genetic diversity for future generations. The ensured sustainability of rice cultivation will contribute to food security and economic prosperity in Tamil Nadu.

4. DATASET PREPARATION

Creating a high-quality dataset is essential for training effective machine learning models in paddy classification. This involves meticulous data collection, organization, and processing. The first step is gathering a diverse collection of paddy rice images. This dataset should be segregated into three subsets: training, validation, and testing. A widely used split allocates 70% of the images for training, 15% for validation, and 15% for testing the model’s performance. This specific study focused on capturing images of traditional rice varieties indigenous to India, including Aruvatham kuruvai, Attur kichili samba, and many others. To ensure image clarity and accurate classification, meticulous cleaning procedures were undertaken.

Fig.1. Traditional rice varieties
(a) Aruvatham kuruvai (b) Attur kichili samba (c) Kallimadiyan (d) Karupu kavuni (e) Kattuyanam (f) Kulivedichan (g) Mappillai samba (h) Poongar i sonamasuri (j) Sreega samba (k) Madumuzhungi (l) Kitchili samba

Before image capture, the paddy seeds underwent a rigorous cleaning process to eliminate impurities and foreign objects. This involved adhering to purity test standards established by ISTA. This process meticulously removes any extraneous seeds, such as those from other crops or different rice varieties, that might have been present in the initial seed lot. Following cleaning, purified seeds of each variety were transported to a designated area for individual sampling.

4.1 IMAGE ACQUISITION SETUP

The cleaned paddy seeds were meticulously arranged within a controlled laboratory environment on a black cloth backdrop. This ensured adequate spacing between individual grains to prevent overlapping in the final images. Smartphone cameras were employed for image capture. Each phone was equipped with an 8MP rear camera and powered by a 1.4GHz quad-core processor. The camera position was maintained at an average height of 15-20 centimeters above the paddy samples to achieve consistent image framing. It's important to note that lighting conditions during image acquisition were not standardized. While this might introduce some variability into the dataset, it can also improve the model's generalizability to real-world scenarios with varying lighting conditions. The captured images were saved in a common JPG format for easy storage and processing. This comprehensive data collection approach lays the foundation for a robust paddy image dataset that can be used to train machine learning models for accurate paddy classification tasks.

5. PROPOSED METHOD

5.1 TRANSFORMING PADDY IMAGES FOR MACHINE LEARNING

Image preprocessing is vital in preparing paddy images for machine learning models. This step refines the raw data into a format that machines can efficiently understand and process. The goal is to improve image clarity, eliminate noise, and potentially highlight features crucial for classification. In this particular study,the preprocessing pipeline involves two key stages:

5.2 COLOR TRANSFORMATION AND GRAYSCALE CONVERSION:

The original RGB images, which are 1109 x 1069 x 3 pixels (representing red, green, and blue channels), are first resized to a uniform dimension of 256 x 256 pixels. This ensures consistency within the dataset. A special technique called bicubic interpolation is used for resizing. This method meticulously preserves the image information during resizing, preventing data loss. Next, the color model is transformed from RGB to YCbCr. This model separates the image data into luminance (Y) and chrominance (Cr and Cb) components. Luminance represents the brightness or grayscale version of the image, while chrominance encodes color information. Since the model focuses on identifying grain characteristics, the grayscale component (Y) is extracted for further processing. This simplifies the data for the machine learning model without discarding valuable information. Finally, the extracted grayscale values are converted into a standard format suitable for machine learning algorithms.

5.3 NOISE REDUCTION WITH A NOVEL TECHNIQUE

The second stage tackles the issue of noise in the images. Noise can arise from various factors during image capture and can hinder the model's ability to make accurate classifications.

To address this challenge, the preprocessing pipeline incorporates a unique denoising method called the NoiseNixie Rejuvenation Filter (NNRF). This filter specifically targets and reduces noise present in the images, resulting in enhanced clarity.

By improving image quality, the NNRF filter paves the way for more effective processing in the subsequent stages of the machine learning pipeline.

In essence, image preprocessing transforms raw paddy images into a refined format that empowers machine learning models to perform accurate classification tasks. The techniques employed in this study, including resizing, color space conversion, and noise reduction, all contribute to achieving this goal.

The denoising algorithm starts by acquiring the dimensions of the input image, essential for subsequent processing steps. Following this, the image undergoes resizing to a standardized 256x256 resolution while preserving its original aspect ratio. This resizing operation ensures consistency in image dimensions across different inputs. Subsequently, the color space of the image is transformed from the RGB model to the YCbCr model. This transformation separates the image into its luminance (Y) and chrominance (Cb and Cr) components, facilitating more efficient denoising operations by isolating the brightness information from color information. The denoising process utilizes the Fast Fourier Transform (FFT) to convert the image into the frequency domain, where noise characteristics are more discernible. The FFT-derived data is then analyzed to calculate the noise scale frequency (sf) and probability density function (pdf). These calculations are pivotal in identifying and quantifying noise patterns within the image. Once the noise characteristics are determined, a Gaussian filter (Gf) is applied to attenuate noise while preserving image details. The Gf is tailored based on the noise scale frequency and probability density function, ensuring effective noise reduction without compromising image quality. Finally, the denoising algorithm produces the denoised image (DR) by applying the Gf to the FFT-transformed image. The resulting denoised image exhibits reduced noise artifacts and enhanced visual clarity, making it suitable for further analysis or presentation purposes. This comprehensive denoising approach addresses both spatial and frequency domain aspects of noise reduction, resulting in superior image quality outcomes. Finally contrast stretching also applied to enhance the contrast of the image and to preserve the edges bilateral filtered Pixel applied.

The NoiseNixie Rejuvenation Filter (NNRF) is an innovative denoising algorithm designed to enhance image quality while preserving critical details like edges. The process begins by determining image dimensions and resizing it to a uniform 256x256 resolution, maintaining aspect ratio to ensure consistency. Color transformation into the YCbCr model separates brightness (luma) from chrominance components, enabling precise noise reduction by focusing on brightness data. The algorithm employs the Fast Fourier Transform (FFT) to convert the image into the frequency domain, where noise patterns and frequencies are analyzed. Using calculated probability density functions (PDFs) and scale frequencies (sf), noise is effectively minimized based on variation thresholds (σ). A denoised image (DR) is then reconstructed through inverse FFT, followed by contrast stretching to enhance intensity ranges, ensuring better visibility of details. Finally, a bilateral filter is applied to refine the output, preserving edges while smoothing noise. This multi-step approach results in sharp, clear images, ready for further processing in applications such as medical imaging, agriculture, or security systems.

Algorithm 1: NoiseNixie Rejuvenation Filter (NNRF)

Input: Image I, gamma $\gamma = 0.5$, sigma $\sigma = 0.5$, Scale Frequency sf, height h, Gaussian Gf.

Output: Denoised Image DR.

Step 1: Calculate image dimensions

Image Dimensions D=Width × Height

Step 2: Resize the image into 256x256

#Calculate the Aspect ratio

$$\text{Aspect Ratio}=(\text{Original Width})/(\text{Original height}) \quad (1)$$

Convert the height and Width into 256X256

$$H_{new}=256/(\text{Aspect Ratio}) \quad (2)$$

$$W_{new}= \text{Aspect Ratio X } 256 \quad (3)$$

Step 3: Transform the color in to YCbCr model

$$Y=0.299R+0.587G+0.114B \quad (4)$$

$$C_b=1/2(B-Y) \quad (5)$$

$$C_r=1/2\ (R-Y) \quad (6)$$

Step 4: Convert Image using FFT Conversion

Define Fast Fourier Transform for Initial Parameters (height and image total number pixels (N))

N = height * width □(7)

Calculate Absolute probability density function (pdf) value of FFT Image with Total Number of Pixels

pdf = np.abs(fft_image) ** 2 / N (8)

Step 5: Calculate image dimension noise scale frequency

sf = fft_image * (pdf > 0) + 1 / ϒ* fft_image * (pdf == 0) (9)

Calculate Probability Density Function for noise variation sigma

pdf = pdf * (pdf > σ ** 2) + σ ** 2 * (pdf <= σ** 2) (10)

Gf = sf * (pdf - σ ** 2) / (pdf - (1 - 1) * σ ** 2) (11)

Step 6: Denoised Image DR result

Obtain the denoised image result (DR) by multiplying Gf with the FFT image:

Result DR = Gf * fft_image (12)

Step 7: Apply contrast stretching

To enhance the contrast of the image by Apply contrast stretching:

$$New\,Intensity(i,j)=\frac{I(i,j)-MinIntensity}{MaxIntensity-MinIntensity} \quad (13)$$

Step 8: Apply Bilateral Filtered Pixel to preserve the Edges

Bilateral Filtered Pixel=

$$\frac{1}{W_p}\sum I(q)\cdot G_s(\|p-q\|)\cdot G_r(|I(p)-I(q)|) \quad (14)$$

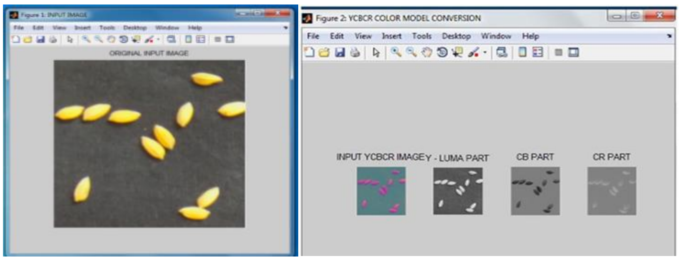

Fig.2. (a) Original Input Image (b) Transformation of RGB to YCbCr color model

The input image, depicted in Fig.2, serves as the foundation of our system. It's resized to 256x256 pixels using bicubic interpolation for consistency and aspect ratio preservation. Next, the RGB image is converted to the YCbCr color model, isolating brightness (Y) from color (Cb and Cr) information. This step is crucial for tasks like denoising and edge detection. By focusing on the Y component, we retain essential visual details. Our NoiseNixie Rejuvenation Filter (NNRF) introduces noise variation (sigma) of 0.5 and luminance correction (gamma) of 0.5, along with height calculation for further processing. The image then undergoes Fast Fourier Transform (FFT) conversion and is subsequently transformed back using Inverse FFT, with adjustments made to account for pixel variation.

6. RESULTS AND DISCUSSION

The proposed system utilizes Python as the primary programming language due to its robust libraries for image processing, including OpenCV and SciPy. TensorFlow or PyTorch frameworks are employed for implementing machine learning models. The software environment requires an OS like Windows 10, Ubuntu 20.04, or higher. Additional dependencies include NumPy, Matplotlib for visualization, and CUDA for GPU acceleration, ensuring efficient processing of complex datasets. The system requires a minimum of an Intel Core i5 processor or equivalent, 16 GB of RAM for handling large image datasets, and an SSD with at least 512 GB storage for faster data access. For enhanced performance, a dedicated GPU such as NVIDIA GTX 1650 or higher is recommended to accelerate computation-intensive tasks like neural network training and Fast Fourier Transform operations.

The denoised image obtained from the Inverse FFT operation is then displayed using an image adjust function, allowing for visual assessment of the denoising results. Notably, the proposed NoiseNixie Rejuvenation Filter (NNRF) achieves the highest Peak Signal-to-Noise Ratio (PSNR) value compared to conventional denoising techniques such as median filter, Gaussian filter, and Wiener filter. Paddy Seed image quality is evaluated using two key metrics: Peak signal-to-noise ratio (PSNR) and Mean Square Error (MSE). PSNR measures the ratio of signal power to noise power, indicating image reconstruction quality. Conversely, MSE quantifies the cumulative squared error between compressed and original images, with lower values signifying reduced error. Figure 3 shows the comparison of PSNR and MSE values of the proposed filter.

7. CONCLUSION

Extracting clear, accurate information from paddy images is essential for successful machine learning classification. A critical step in achieving this is noise reduction. Noise can corrupt images during capture and hinder a model's ability to make precise distinctions. This study introduces the NoiseNixie Rejuvenation Filter (NNRF), a novel method that outperforms traditional denoising techniques like median, Gaussian, and Wiener filters. The NNRF method incorporates two key parameters:

- **Noise variation (sigma)**: Set at 0.5, this parameter allows the filter to effectively target and remove noise without affecting the underlying image data.
- **Luminance correction (gamma)**: This value, also set at 0.5, ensures that the filter preserves the image's brightness levels during denoising.

The filter calculates the image height to tailor its operation to the specific image dimensions. This combination of parameters empowers the NNRF method to achieve exceptional noise reduction while safeguarding image integrity. The effectiveness of the NNRF method is demonstrably evident. When applied to paddy images, the resulting denoised images exhibit a remarkable Peak signal-to-noise ratio (PSNR) value of 59.9883. PSNR is a standard metric used to quantify the quality of denoised images. A higher PSNR signifies a greater improvement in image clarity. These impressive results solidify the NNRF method's position as a powerful tool for image enhancement. Its ability to remove noise while maintaining image quality makes it valuable for various applications that demand high-fidelity image processing, such as medical imaging and autonomous vehicles. Beyond paddy image classification, the NNRF method holds promise for enhancing image quality in diverse fields. Future work will focus on integrating advanced deep learning models to enhance classification accuracy and scalability for diverse grain types. Additionally, exploring real-time processing capabilities using edge computing devices will improve deployment in field environments. Efforts will also include incorporating multispectral imaging to capture richer feature sets and refining the pipeline for other agricultural and industrial applications.

REFERENCES

[1] R. Singh and R. Gupta, "Rice Type Classification using Proposed CNN Model", Proceedings of International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies, pp. 1-6, 2023.

[2] I. Firmansyah, R. Rosnelly and W. Wanayumini, "Inception-V3 Versus VGG-16: in Rice Classification Using Multilayer Perceptron", *Proceedings of International Conference on Information Science and Technology Innovation*,Vol. 2, No. 1, pp. 1-5, 2023.

[3] N. Tran-Thi-Kim T. Pham-Viet I. Koo, V. Mariano and T. Do-Hong "Enhancing the Classification Accuracy of Rice Varieties by Using Convolutional Neural Networks", *International Journal of Electrical and Electronic Engineering and Telecommunications*, Vol. 12, No. 2,150-160, 2023.

[4] B. Arora N. Bhagat, L.R. Saritha and S. Arcot, "Rice Grain Classification using Image Processing and Machine Learning Techniques", *Proceedings of International Conference on Inventive Computation Technologies*, pp. 205-208, 2020.

[5] H. Ning, S. Liu, Q. Zhu and T. Zhou "Convolutional Neural Network in Rice Disease Recognition: Accuracy, Speed and Lightweight", *Front. Plant* Science, Vol.14, pp. 1-7, 2023.

[6] C. Sindhu, S. Sasmitha, P. Tamilmani, C. Udaysriram and V.V. Gowri, "Rice Grain Type and Grading of Rice Grains using Image Processing", *International Journal of Research in Engineering, Science and Management*, Vol. 4, No. 7, pp. 1-7, 2021.

[7] V.T. Hoang, D.P. Van Hoai, T. Surinwarangkoon, H.T. Duong and K. Meethongjan, "A Comparative Study of Rice Variety Classification based on Deep Learning and Hand-Crafted Features", *ECTI Transactions on Computer and Information Technology*, Vol. 14, No. 1, pp.1-7, 2020.

[8] K. Kiratiratanapruk, P. Temniranrat, W. Sinthupinyo, P. Prempree, K. Chaitavon, S. Porntheeraphat and A. Prasertsak, "Development of Paddy Rice Seed Classification Process using Machine Learning Techniques for Automatic Grading Machine", *Journal of Sensors*, pp. 1-7, 2020.

[9] V.A. Patel and M.V. Josh, "Convolutional Neural Network with Transfer Learning for Rice Type Classification", *Proceedings of International Conference on Machine Vision*, pp. 282-289, 2018.

[10] R.A. Dar, D.M. Bhat, A. Assad, Z.U. Islam, W. Gulzar and A. Yaseen, "Classification of Rice Grain Varieties using Deep Convolutional Neural Network Architectures, pp. 1-7, 2022.

[11] Y. Abbaspour-Gilandeh, A. Molaee, S. Sabzi, N. Nabipur, S. Shamshirband and A. Mosavi, "A Combined Method of Image Processing and Artificial Neural Network for the Identification of 13 Iranian Rice Cultivars", *Agronomy*, Vol. 10, No. 1, pp. 1-6, 2020.

[12] H. Alshehri, M. Hussain, H.A. Aboalsamh and M.A. Al Zuair, "Cross-Sensor Fingerprint Matching Method based on Orientation, Gradient and Gabor-Hog Descriptors with Score Level Fusion", *IEEE Access*, Vol. 6, pp. 1-7, 2018.

[13] B.S. Anami, N.N. Malvade and N.G. Hanamaratti, "An Edge Texture Features based Methodology for Bulk Paddy Variety Recognition", *Agricultural Engineering International: CIGR Journal*, Vol. 18, No. 1, pp. 399-410, 2016.

[14] B.S. Anami, N.N. Malvade and S. Palaiah, "Automated Recognition and Classification of Adulteration Levels from Bulk Paddy Grain Samples", *Information Processing in Agriculture*, Vol. 6, pp. 47-60, 2019.

[15] B.S. Anami, N.N. Malvade and S. Palaiah, "Classification of Yield Affecting Biotic and Abiotic Paddy Crop Stresses using Field Images", *Information Processing in Agriculture*. Vol.7, No.2, pp. 272-285, 2020.

[16] V.M. Butardo and N. Sreenivasulu, "Improving Head Rice Yield and Milling Quality: State-of-the-Art and Future Prospects", *Rice Grain Quality: Methods and Protocols*, Vol. 1892, pp. 1-7, 2018.

[17] K.W. Chee and S.S. Teoh, "Pedestrian Detection in Visual Images using Combination of HOG and HOM Features", Proceedings of International Conference on Robotics,

Vision, Signal Processing and Power Applications: Enabling Research and Innovation Towards Sustainability, pp. 591-597, 2019.

[18] T. Mushiri, L. Tende "Automated Grading of Tomatoes using Artificial Intelligence: The case of Zimbabwe", *AI and Big Data's Potential for Disruptive Innovation, IGI Global*, pp. 216-239, 2020.

[19] H. Zhang, J. Wang, Z. Sun, J.M. Zurada and N.R. Pal, "Feature Selection for Neural Networks using Group Lasso Regularization", *Transactions on Knowledge and Data Engineering*, Vol. 32, No. 4, pp. 59-73, 2019.

[20] M.M. Tin, K.L. Mon, E.P. Win and S.S. Hlaing, "Myanmar Rice Grain Classification using Image Processing Techniques", *Proceedings of International Conference on Big Data Analysis and Deep Learning Applications*, Vol. 744, pp. 324-332, 2018.

[21] M. Uddin, M.A. Islam, M. Shajalal, M.A. Hossain and M.S. Yousuf, "Paddy Seed Variety Identification using t20-Hog and Haralick Textural Features", *Complex and Intelligent Systems*, Vol 8, No. 1, pp. 57-71, 2022.

[22] K. Kiratiratanapruk, P. Temniranrat, W. Sinthupinyo, P. Prempree, K. Chaitavon, S. Porntheeraphat and A. Prasertsak, "Development of Paddy Rice Seed Classification Process using Machine Learning Techniques for Automatic Grading Machine", *Journal of Sensors*, pp. 1-7, 2020.

[23] A. Chaugule and S.N. Mali, "A New Method using Feature Extraction for Identifying Paddy Rice Species for Quality Seed Selection", *The Imaging Science Journal*, Vol. 65, No. 4, pp. 226-238, 2017.

[24] M.A. Islam, M.R. Hassan, M. Uddin and M. Shajalal, "Germinative Paddy Seed Identification using Deep Convolutional Neural Network", *Multimedia Tools and Applications*, Vol. 82, pp.1-7, 2023.